Subjective Well-Being in a Spatial Context

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Chapter 2

Neighbourhood income and SWB

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Abstract

Studies relating income to subjective well-being have found that both absolute and relative income determine individual well-being. This article assesses the effect of relative income on subjective well-being, and the spatial scale on which this comparison takes place. This study employs spatial data on individual well-being, health, socio-economic status, and psychometrics. The findings suggest that relative income is a significant predictor of subjective well-being. The relationship is negative for high income individuals, but absent or reversed for low income individuals showing an asymmetric relationship. The spatial scale for the comparison effect is small, with a bandwidth of 100 metres providing the best fit.

2.1 Introduction

While the socio-economic position of an individual relative to their peers is an established factor for explaining subjective well-being (SWB), the question of how this reference group is constructed is still debated. Several studies provide suggestions as to how this might be constructed, using regional definitions such as national or larger sub-national areas (c.f. Diener et al., 1993), combined with bracketing by age or education (Clark and Oswald, 1996), or through self-report (Ma et al., 2018). The literature on conspicuous consumption suggests that the peer-effect may have a spatial component (c.f. Hicks and Hicks, 2014), with closer neighbours experiencing a stronger effect than those living at a greater distance.

To date very little research has been done on the spatial extent and dissipation of this relative income effect. This chapter examines three interrelated questions, namely: (i) how does the socio-economic position of an individual person relative to that of their neighbours affect the well-being of the individual, (ii) on what spatial scale does any observed neighbourhood-well-being effect operate, and (iii) over what spatial scale does it dissipate?

For this study we use measures of spatial autocorrelation (Anselin, 1995) to determine the individual's household income relative to their neighbours, and we examine the effect this has on individual well-being. We then estimate a series of neighbourhood distance bandwidths and compare the model fit as an indicator of the spatial extent at which any comparison effect takes place. Besides the spatial construction of relative income, there are various paradoxes and pitfalls in well-being research which need to be carefully controlled for when addressing these questions. In this chapter we carefully control for such factors by employing data from a large scale, spatially disaggregated survey on health and well-being (N=44,665) in the North of the Netherlands. This survey provides us with highly specific self-reported health and psychometric data to control for known confounders of SWB. These data allow us to compare these individual-specific measures with respect to the socio-economic status of their immediate neighbours.

Our findings suggest that relative income is a significant predictor of SWB, but the relationship is asymmetrical for individuals in households with higher or lower incomes. For individuals in high-income households, relative income is inversely correlated with SWB, while for individuals in low income households this effect is absent or reversed. The spatial scale for the comparison effect is small, with a nearest neighbour bandwidth of 100 metres providing the best fit. This suggests that very local neighbourhood effects dominate well-being.

The rest of the chapter is structured as follows. Section 2 discusses the relationship between well-being and income, followed by a discussion on the peer-effect of income on well-being. Section 3 establishes the spatial nature of the peer-effect and the current lack of spatial analyses into these topics. Section 4 describes the methods and data used in this study. Section 5 presents our empirical results and section 6 provides a brief discussion and conclusions.

2.2 Income, well-being, and peer-effects

The new economics of happiness has in recent years meant that studies of happiness, SWB and life-satisfaction have increasingly been used beyond sociology and psychology (Frey, 2008). One of the first to link SWB and income was Easterlin (1974), who observed a set of paradoxical relationships between happiness and income. The Easterlin paradox consists of three observations. First, cross-sectional differences in per capita income within a country are positively correlated with increased happiness. Second, cross-sectional differences in per capita income between countries are positively related to happiness. Third, longitudinal changes in income per capita in a country (i.e. for example the rise in per capita income in the US post second world war) do not correspond with increases in happiness over time. While the first two observations are as might be expected from standard utility theory, the third is not. The notion of comparative utility has therefore been used to help explain this paradox, and this relies on the assumption that an individual's utility (taken to correspond to an individual's happiness, c.f. Frey and Stutzer, 2002) is a construct of both the individual's absolute consumption as well as the individual's relative consumption (Luttmer, 2005). The absolute consumption dimension in this comparative utility function incorporates the first two observations made by Easterlin, regarding a positive link between income and well-being both within and between countries. Meanwhile, the relative dimension of comparative utility controls for the third Easterlin (1974) observation and this dimension remains constant with relative wealth, even if absolute wealth increases.

A growing body of empirical evidence supports this notion of comparative utility as underpinning indices of well-being (Ma et al., 2018; Clark et al., 2008; Hagerty, 1999; Blanden et al., 2005). One of the solutions put forward (Easterlin, 1974; McBride, 2001) is to measure well-being by weighting individual utility (as a function of consumption) by the consumption of the rest of the cross-section, thereby controlling for the whole population being better off

$$U_i = U_i \frac{C_i}{\sum_{j \in J} \alpha_{ij} C_j} \tag{2.1}$$

where U_i is an individual's utility, C_i an individual's consumption, a_{ij} the weight given by i to j's consumption, C_j is j's consumption.

For a certain household income, individuals comparing to a reference group with a high household income should report lower levels of SWB, and vice versa (Luttmer, 2005). Following this type of logic, the measures of self-reported well-being in the various published studies are all sensitive to the reference group chosen (Ball and Chernova, 2008; Veenhoven, 2012), because the choice of reference group determines the denominator in equation 2.1. The available published findings variously include as the appropriate reference group national or sub-national administrative regions (Diener et al., 1993), or more individual notions of cohort-comparisons (i.e. brackets of age, or education and race McBride, 2001; Clark and Oswald, 1996). Except for Diener et al. (1993), these studies all find a positive effect of comparative utility, although the results differ according to the reference group chosen, thereby raising the questions we address in this study.

2.3 Geographical aspects of the peer-effect

For social comparisons to take place, one of the crucial steps is to observe similarities and differences between one's own and the peer's patterns of consumption (Diener et al., 1999). Solutions of considerable geographical size (e.g. national), fail to consider the spatial dimension of these comparisons. Most likely an individual's ability to compare their own quality of life situation with peers is very limited when the peer group is very large in terms of population and area (Diener et al., 1999). Following Tobler's Law (Tobler, 1970), there are strong arguments to suggest that how an individual feels in terms of SWB will be more heavily influenced by the experiences of close neighbours than people who are distant to the individual.

What we mean by close or distant is as yet undefined, as is the spatial scale over which such a comparison (comparative utility) effect is likely to be statistically significant. On this point Luttmer (2005) finds evidence for a comparison effect in areas of at least 100,000 people. Individuals are, however, unlikely to accurately observe their relative rank within such a large population. Bringing the size down to smaller administrative regions partially solves this problem. Smaller study-regions will more closely reflect the neighbourhood as experienced (Briggs, 1997). Indeed, Knight et al. (2009) find a positive and significant effect for comparative utility (in the Chinese context) and show that the (stated) reference group for respondents was on a much smaller spatial scale, in this case, their village. However, individual interpersonal comparisons may be more realistic on much smaller scales, such as functional neighbourhoods, extending to only about 4 houses in each direction (Gans, 2017). If this were indeed the case, estimating a comparison effect for the functional neighbourhood with administrative data would not be possible, because boundaries of experience are more fluid and context dependent (Campbell et al., 2009) and also because the tiny functional neighbourhood would not coincide with the larger boundaries of the administrative region.

In this study we argue for an operationalization of the peer-group based on geographical distance. In particular, following Tobler's (1970) emphasis on proximity in spatial relations, we argue that the peer-effect will be most prominent over smaller spatial distances (c.f. Winkelmann, 2012).

The preceding discussion leads to the two expected relations between SWB, household income, and relative household income under consideration in this study. First, controlling for an individual's household income (which is positively related to SWB) a higher neighbourhood household income is expected to lead to lower SWB. Second, the comparative income effect is expected to decay along with distance to residence as a function of the observability of the peer's household income levels.

2.4 Method and data

2.4.1 Relative income

In terms of the individual person's positioning relative to their neighbourhood comparison group, the use of individual data instead of administrative regions does bring with it a complication of how to determine the individual's relative socio-economic position. When determining the relative position in administrative regions, an individual's z-score within the administrative region can be calculated. However, using individual data, this neighbourhood, and consequently, this z-score is not readily available. Therefore, in order to determine the relative position of an individual compared to their neighbourhood this study uses the Local Moran's I (LMI). The LMI is calculated as follows,

$$I_i = z_i \sum w_{ij} z_j \tag{2.2}$$

where I_i is the LMI test statistic for each individual in the sample, z_i represents the deviation from the population mean for individual i. The individual z-score is then multiplied with the z-transformed weighted sum of the j individuals living within the specified bandwidth (Anselin, 1995).

The intuition for the I_i statistic is that negative values indicate a dissimilarity between individual i and j neighbours (either a negative z_i with positive neighbours, or a positive z_i with negative neighbours). Similarly, positive values are the result of individual i and neighbours j being the same sign. The I_i statistic is subsequently compared to the expected value and variance, providing probability estimates (Anselin, 1995). Low outcomes of the I_i statistic are combined with the standardized measurement variable (i.e. household income) to determine whether the case in question is a positive or negative outlier, or rich in a poor neighbourhood or poor in a rich neighbourhood respectively. Similarly, for positive I_i values this combination allows us to determine whether a case is part of a rich cluster or a poor cluster.

Linking back to the comparison component of household income, for a given household income there are three types of spatial clustering outcomes. For a well-off household with relatively affluent neighbours, the LMI value will be high and positive, if the neighbours are less affluent or more mixed, the LMI value will be closer to zero, and if the neighbours are relatively poor, the LMI value will be large and negative. Controlling for the individual's household income, clusters of high-income households should have a negative effect on individual SWB, *ceteris paribus*, as the individual's household income relative to the neighbourhood is lower than those with the same household income who do not live in a cluster of high-income households. This would reflect the negative externality of neighbourhood income (Luttmer, 2005). An individual with a high household income in a region with relatively poorer households would have a relatively high comparative income, which would then lead to a higher SWB outcome.

Similarly, clusters of low household income should have a positive effect on individual SWB, as the relative household income of the individual compared to the reference group is now higher [1]. The important point here is that the use of the LMI as a measure of relative household income allows for the separation of the effects for relatively affluent and less affluent neighbourhoods, as well as for relatively rich and relatively poor households.

One of the most important considerations for estimating a measure of spatial autocorrelation is the nearest neighbour function (Griffith et al., 2003). There are three main operationalizations of the nearest neighbour function. First, there is the k-nearest neighbours function, which provides a nearest neighbour matrix which holds the same number of (nearest) neighbours per feature. This method of estimating proximity is useful when providing a full set of nearest neighbours is more important than the spatial extent of the nearest neighbour set. Second, there is a class of nearest neighbour functions which take into account the spatial structure of the features, such as contiguity or networks. This type of classification is used when the spatial structure of the points is of primary interest, e.g. through transport links. The third method of estimating proximity is through a distance threshold. This method utilizes a predefined set of distance bandwidths in order to measure the spatial extent at which a process is still valid. This method is particularly useful when the spatial extent of the process under

[1] Interestingly, McBride (2001) puts forward the argument that, as the Easterlin paradox also holds for poorer countries, the comparison effect is also expected to function among less affluent individuals. However, this assertion that the country-wide comparison effect is permutable to the individual (or sub-groups of individuals) is as yet left untested

consideration is most important (Bivand and Piras, 2015; Bivand et al., 2013).

Given the research question outlined at the beginning of the chapter, the method most appropriate for our study is the distance threshold measure of nearest neighbour estimation. To estimate the extent at which peer-effect still occurs, we estimate the nearest neighbour sets at a series of bandwidths, starting at 100 metres, through 250 metres, 500 metres, 1000 metres, and from there at 500 metre intervals up to 5000 metres. Estimating the LMI requires sufficient cases to be entered as neighbours in order to determine the relative position. Using smaller bandwidths means more cases will have insufficient neighbours, for instance, at the 100m interval the number of cases usable for the study drops by 6,315. Going to 50m would lead to 15,216 cases to be removed from the analyses. Dropping the number of cases by this amount also disproportionately affects the number of usable cases in rural areas, leading to an urban bias. In order to limit this potential bias, this study uses the 100m bandwidth as the lower threshold of estimation.

Using continuous nearest neighbour distances (0-100, 0-250, 0-500, and so on) means that if the comparison effect takes place on relatively small spatial scales, consecutive spatial scales will borrow significance from the smaller scales. This is especially the case when using inverse-distance nearest neighbour weights. To alleviate this issue we estimate the model in three distinct ways: First, by using concentric, but mutually exclusive, distance bandwidths (0-100, 100-250, 250-500, etc.). This estimation separately shows the relative positions between the individual and the neighbours at subsequent distance bandwidths. The OLS specification follows the format

$$SWB = CONF + SES + MI_{d=0-100} + MI_{d=100-250} ... MI_{d=4500-5000} \tag{2.3}$$

where $CONF$ and SES are the individual's socio-economic status and other known confounders, and MI_d are the LMI values, separated into the four types of relative positions, at distance interval d. Separate models are estimated including the MIs for all bandwidths up to each distance interval.

Second, we estimate the regressions with the more conventional overlapping nearest neighbour specification, 0-100 metres, 0-250 metres, and so on. For these bandwidths we estimate two sets of models, first including the relative positions of the individual for all bandwidths up to each distance interval, such that

$$SWB = CONF + SES + MI_{d=0-100} + MI_{d=0-250} ... MI_{d=0-5000} \tag{2.4}$$

which gives the effect of each larger interval, controlling for the smaller, nested intervals. Using this specification allows us to separate the effects of increasingly large neighbourhoods, while controlling for the effect of the closest neighbours.

Third, we estimate the regressions using this (overlapping) nearest neighbour specification, but in the estimations we include each distance threshold separately, such that

$$SWB = CONF + SES + MI_{0-d} \tag{2.5}$$

which includes only one term for the LMI's. These specifications allow us to measure the effect of increasingly large neighbourhood specifications separately.

Following Burnham and Anderson (2002), the likelihood of the models is then compared using the AIC, using the formula for equivalent likelihood

$$LH_i = e^{\frac{AIC_{min}-AIC_i}{2}} \tag{2.6}$$

here, in a series of models, LH_i is the likelihood of model i, AIC_{min} is the lowest AIC in the series, and AIC_i is the AIC of model i. This results in a probability estimate that model i is equivalent to the best model in the series. Values of LH_i smaller than 0.05 allow models to be rejected.

2.4.2 Measuring subjective well-being

In this chapter we use self-reported well-being scores. Self-reported well-being allows for individual variation in well-being as an outcome and makes no assumptions about the interpersonal comparability of the determinants of well-being or the efficiency with which preferences are satisfied. As this study is concerned with the effect of the relative position of the individual rather than the absolute position regarding the known covariates of well-being, this heterogeneity in the outcome variable is a requirement. However, the use of SWB data in research is not without its concerns. There are three main concerns when using self-reported happiness data in research. First there is the question whether individuals can reasonably accurately estimate their own happiness. Veenhoven (2012) provides an overview of literature dealing with the validity of the happiness question and concludes that happiness questions are generally well understood and “measure what they are supposed to measure” (Veenhoven, 2012). In addition, there is a growing body of empirical evidence that shows that happiness ratings are related to measurable physiological correlates with happiness, such as smiling, blood pressure and heart rate, and brain activity in regions associated with happiness (Alesina et al., 2004). The second concern is that differences in SWB may occur due to cultural differences. Again, Veenhoven (2012) reports a series of cross-national correlations showing that it is unlikely that there is a cultural bias in happiness responses. Thirdly, SWB may be influenced by adaptation. On this point, self-reported health is found to be strongly correlated with SWB, while the same is not true for objective measures of health (Diener et al., 1999). The problem with using an objective measure of health is that the effect of health on well-being is mitigated through adaptation, where the effect of a downward change in health lessens over time. In contrast to objective measures of health, self-reported measures of health show a strong positive correlation with SWB (Lucas et al., 2008).

2.4.3 Confounders of SWB

To control for undue influences we estimate our regressions with a series of known confounders of SWB. As previously mentioned, we need to control for self-reported health. In addition to health, an individual's psychometric characteristics are an important predictor of well-being: Frijters and Beatton (2012) show that SWB is at least partly attributable to a predisposition to be happy and Karademas (2006) shows that self-efficacy is related to individual functioning and consequently life satisfaction. Age and well-being have a complicated relationship, with some arguing for a U-shaped relationship (Blanchflower and Oswald, 2008) while Frijters and Beatton (2012) show this U-shape disappears when individual fixed effects are properly controlled for. A person's social interactions are also known to correlate with well-being. Relationship status and well-being correlate, with empirical evidence suggesting that married people are happier than people who are not married (Lucas et al., 2003, 2008), although the direction of causality is still up for debate (Stutzer and Frey, 2006). Similarly, both employment status (Korpi, 1997) along with the number and quality of social ties are positively correlated with SWB (Lucas and Dyrenforth, 2006; Lucas et al., 2008).

2.4.4 Lifelines dataset

To control for these individual characteristics this study draws on an extensive survey conducted in the North of the Netherlands. The Lifelines Biobank survey is designed to assess multi-morbidity and intergenerational factors relating to morbidity. The survey contains a wide variety of data, including genetics, physiological measurements, and a repeated survey design to assess behavioral factors. Prospective participants (aged 25-50) were initially approached through their general practitioner, with exclusion criteria related to mental illness, limited life-expectancy, or insufficient knowledge of the Dutch language. People who did not receive an invitation could also self-register through the website. The main incentive for participation was a free comprehensive health check.

Parents, siblings, and children of participants were subsequently invited to participate in the study. Cohort profiles by Klijs et al. (2015) and Scholtens et al. (2015) show the Lifelines cohort to be broadly representative of the population of the North of the Netherlands. Although initial pilots for the Lifelines survey were run from 2006, some changes were made to variables in the survey. As a result, the present study contains data from 2008 to 2012 for which the phrasing of the questions was consistent.

The respondent's living address is georeferenced in the Lifelines survey using their home addresses. Due to measurement constraints on our spatial model, each individual is required to have a unique geocoded address, and respondents from the Lifelines survey without a georeferenced place of residence were excluded from our research [2]. The Lifelines survey predominantly focuses on the North of the Netherlands, and the majority of the participants (44,665) were living in the provinces of Groningen, Fryslân, and Drenthe.

In our research, the respondents outside of the North of the Netherlands were excluded for two reasons. First, the density of the respondents outside of the North of the Netherlands is much lower than that of respondents inside the main study area. Given that this study focuses on a nearest neighbours function to determine the spatial autocorrelation, this reduced density could affect the optimum bandwidth size estimation. The data outside of the North of the Netherlands does not have the resolution required for estimating the spatial autocorrelation on a small enough scale to be meaningful. Second, respondents outside of the original study area require household mobility in (at least) one of the generations under consideration, which could result in a selection bias.

2.4.5 Operationalization

The Lifelines questionnaire contains background data on the participants' socio-economic status, psychometric data, and self-reported health. From the questionnaire we use the RAND-36 (also known as the Medical Outcome Survey 36 Short Form, MOS 36-SF) survey tool, which measures eight constructs of well-being outcomes, namely: physical functioning; role limitations due to physical problems; social functioning; bodily pain; emotional well-being; role limitations due to emotional problems; fatigue; and health (Hays and Morales, 2001).

For our SWB dependent variable we use the subjective emotional well-being score from the RAND-36 survey tool. This construct contains questions on whether an indi-

[2] The Lifelines survey set up explicitly focuses on obtaining data on an individual's family, resulting in 9,470 cases of people with shared addresses. These shared datapoints were excluded from the study at random.

vidual feels happy, sad, depressed, or anxious (Hays and Morales, 2001). The items are consequently weighted according to the RAND-36 guidelines, providing a 0-100 score on emotional well-being. The descriptive statistics for the variables included in the models are in table 2.1.

We control for the relationship between well-being and the self-efficacy of the individual by adding data on the positive and negative affect to the right-hand side of the model. The positive and negative affect scales (PANAS: Crawford and Henry, 2004; Watson et al., 1988) measure the mood of the individual, with items relating to curiosity, enthusiasm, excitement, determination on the positive side, and guilt, shame, nervousness, distress on the negative side. As Watson et al. (1988) note, an important component of the PANAS measurement tool is the timespan for which respondents rate the items. A shorter timespan provides results indicative for current mood (such as today, or yesterday), whereas longer timespans exhibit trait-like stability. In the Lifelines questionnaire the timespan for which individuals answered the PANAS questions was “the past four weeks”.

WORK and employment status are included in the model as a dummy variable with the reference category people working full-time. This variable is originally a categorical variable, with non-exclusive categories. In the model this chapter distinguishes between the effects of unemployment, unemployment while looking for work, receiving benefits, receiving a pension, students, homemakers, and people receiving disability benefits. RELATIONSHIP status is included in the model as a categorical variable for those who currently have a partner and people who have been widowed or divorced. The reference category is people who are not in a relationship (but have not been widowed or divorced). AGE is recorded as the age in years at the time of the survey. INCOME is included in the model as disposable household income, with the first category at 0-750 euros per month, the second category 750 euros to 1000 euros, from there at 500 euro intervals until 3500. The final category is 3500 euros or more disposable household income per month. As the LMI requires normalization of the measurement variable, the scale of measurement on the original variable has to be equidistant. The household income variable is recoded to fit the requirements of equidistance to such that 1.5 relates to the threshold of €750, 2 relates to €1,000, 3 to €1,500, etc. The regressions were run with and without the highest income category as the highest category contains no upper bound. No differences in sign and significance were observed between models with and without the highest income category. The results presented in this chapter include all income categories.

Table 2.1: Descriptives of variables in model

Variable	n	mean	sd	median	range
RANDEMO	38350	78.97	13.94	80.00	100.00
Emotional role-limitations	38350	67.38	19.82	75.00	75.00
Fatigue	38350	66.78	17.04	70.00	100.00
Health	38350	68.26	12.52	70.00	95.00
Pain	38350	84.63	18.99	90.00	100.00
Physical health	38350	91.14	13.65	95.00	100.00
Physical role-limitations	38350	86.43	29.51	100.00	100.00
Social functioning	38350	86.97	18.44	100.00	100.00
Positive Affect	38350	3.54	0.42	3.60	4.00
Negative Affect	38350	2.08	0.53	2.00	4.00
Sex	38350	0.57			
Relationship (1=Yes)	38350	0.50			
Divorced or widowed (1=Yes)	38350	0.03			
Part time work	38350	0.45			
Unemployed	38350	0.30			
Disability benefits	38350	0.03			
Other benefits	38350	0.01			
Homemaker	38350	0.04			
Student	38350	0.06			
Pension	38350	0.04			
Income	38350	5.36	1.88	5.00	6.50
Age	38350	43.08	11.18	43.00	71.00
Year of survey					
Y:2008	2752				
Y:2009	4669				
Y:2010	8120				
Y:2011	13449				
Y:2012	9360				

Table 2.2: Item reliability RAND

Item	Cronbach's Alpha
SWB	0.83
Emotional role-limitations	0.85
Fatigue	0.77
Health	0.73
Pain	0.85
Physical health	0.86
Physical role-limitiations	0.89
Social function	0.79

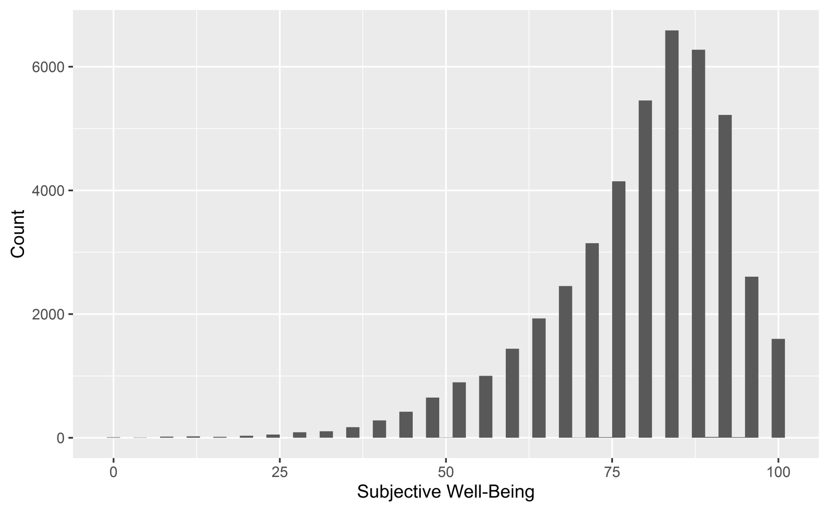
2.5 Results

2.5.1 Reliability and baseline model

The RAND-36 data is tested for item-reliability scores using a Cronbach's Alpha. Scores above 0.7 are considered acceptable and scores above 0.8 considered good (DeVellis, 2003). All the RAND-36 survey items test above the acceptable threshold (see table 2.2), confirming that the RAND constructs using these survey items are internally consistent.

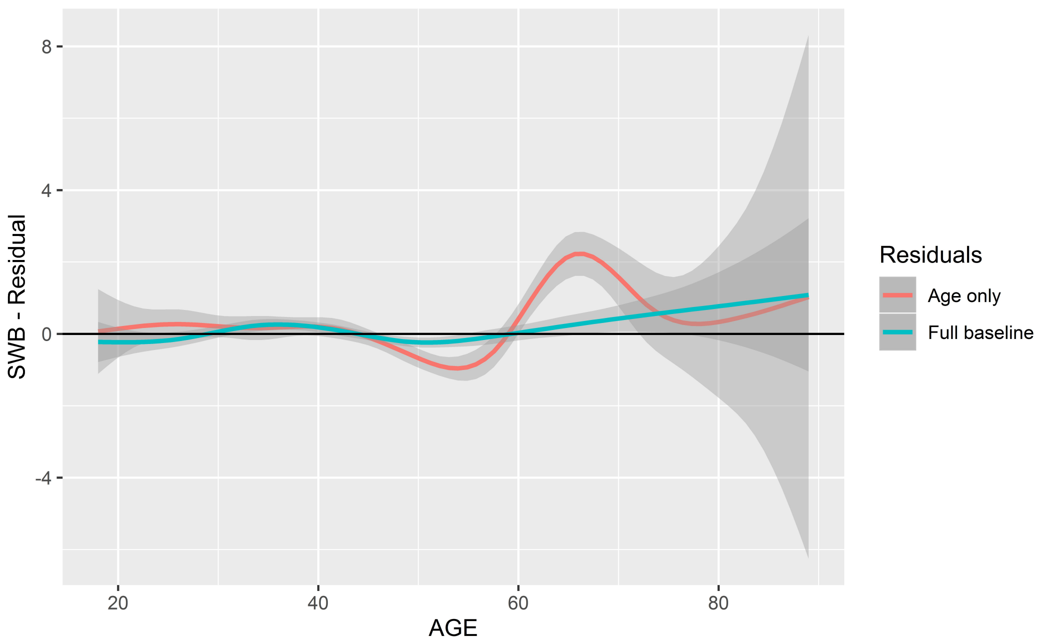
Figure 2.1 shows the distribution of SWB in this dataset. The distribution is left-skewed, because most people are relatively happy while a small number of people are unhappy. There appears to be a ceiling effect, similar to the findings in Hopman et al. (2000) which limits the availability in left-hand-side variance at higher levels.

Figure 2.1: Distribution of SWB



Given the earlier comments on the relationship between age and well-being, we check to see if there is a correlation. Figure 2.2 shows the residuals from a bivariate regression between age and SWB. In this model, age is positively associated with SWB (coefficient 0.076). The observed SWB is lower than predicted from around 50 years of age but rises sharply around retirement age and subsequently declines back to the predicted values. When we control for the confounders mentioned earlier in our baseline model (table 2.3) we find that age is negatively associated with SWB. Separately, we find that there is no evidence for a polynomial relationship (results not shown). As Frijters and Beatton (2012) note, the age-SWB correlation is probably in part down to individual fixed effects, which we can proxy for (e.g. the affect scales) and subjective characteristics such as health and social interactions. Particularly in old age, the variance of the residuals (figure 2.2) is smaller once personal characteristics are controlled for. Starting around the age of retirement, we still find a positive uptick of the residuals showing that this model predicts lower SWB than is observed (although lower numbers of respondents at these ages mean we treat this result with caution).

Figure 2.2: Adjusted distribution of SWB



The baseline model (see table 2.3) shows that all RAND constructs are significant predictors of SWB with the exception of pain. All RAND constructs are coded from low to high with higher values indicating better perceived health status (so high for fatigue means a person experiences little to no fatigue). The RAND constructs for emotional role, fatigue, health, physical problems, and social functioning are positive and significantly related to SWB. The RAND construct of physical role limitations is significant and negatively correlated with well-being. One possible explanation is that

Table 2.3: Baseline model

BASELINE	Coefficient	Standard Error
(Intercept)	48.2430***	(0.561)
Emotional role-limitations	0.137***	(0.002)
Fatigue	0.265***	(0.003)
Health	0.041***	(0.003)
Pain	0.000	(0.003)
Physical health	0.053***	(0.004)
Physical role-limitations	-0.041***	(0.002)
Social functioning	0.167***	(0.003)
Positive Affect	2.680***	(0.097)
Negative Affect	-7.781***	(0.084)
Sex	-0.048	(0.090)
No relationship (ref)		
Relationship (1=Yes)	0.482***	(0.081)
Divorced or widowed (1=Yes)	-1.813***	(0.231)
Full time work (ref)		
Part time work	0.115	(0.094)
Unemployed	-1.319***	(0.227)
Disability benefits	0.130	(0.236)
Other benefits	-1.553***	(0.354)
Homemaker	0.317 †	(0.188)
Student	-1.006***	(0.172)
Pension	1.091***	(0.215)
Income	0.172***	(0.022)
Age	-0.018***	(0.004)
R^2:	0.667	
AIC:	312,579.4	
*** - $p < 0.001$, ** - $p<0.01$, * - $p<0.05$, † - $p<0.10$		

using all RAND constructs introduces multi-collinearity to the model. We check for this using variance inflated factors (VIF) and find it is not a problem in any of the models (all VIFs are between 1.28 and 2.32). The positive and negative affect variables provide plausible coefficients and signs in all models where they are included, with positive affect positively correlated with SWB and negative affect returning a negative sign for the coefficient. This is in line with the results by Frijters and Beatton (2012) who suggest that personal fixed effects related to momentary happiness and self-efficacy contribute to SWB.

The socio-economic and background variables show there is no difference between the sexes related to SWB. People in relationships report higher well-being than those not in relationships, with those experiencing divorce or widowhood the least happy. The employment variables return plausible coefficients. The reference group of the employment dummies is those currently in employment. People who are unemployed (and looking for work) and those receiving general benefits report lower SWB than those currently working, which is in line with the literature. Homemakers are no less happy than those working, and those receiving disability benefits are also no less happy than those currently working. Students are less happy than those in work, and pensioners are happier.

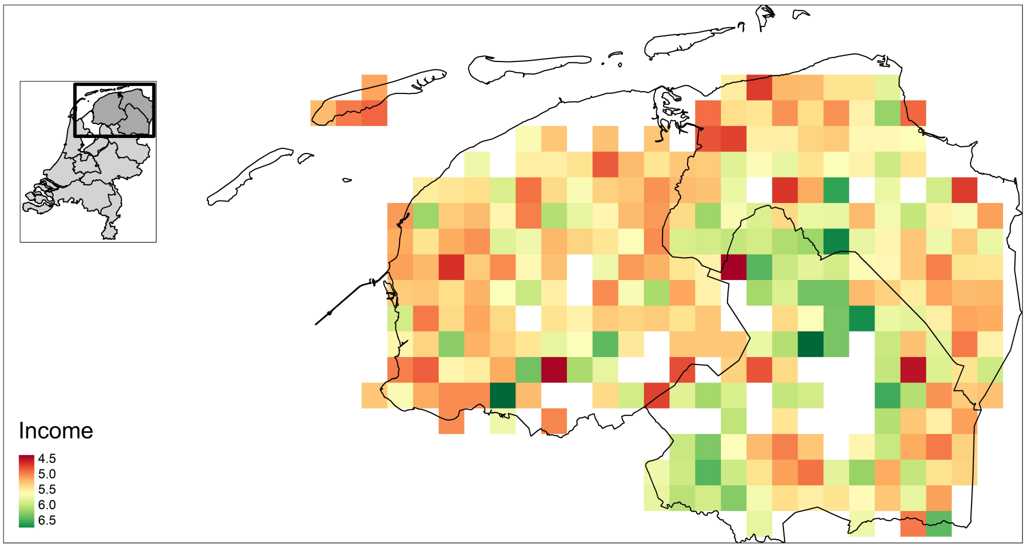
2.5.2 Spatial peer-effect models

Figure 2.3 shows the spatial distribution of the household income variable. The smoothing of the distribution caused by the rastering [3] means that the study area appears rather homogenous.

Figure 2.4 a shows the significantly high clusters of household income at the 100m neighbourhood threshold, with values representing the percentage of people in a high-income cluster per raster-cell (with sides of 5 kilometres). This map serves two purposes. First, it shows that there is indeed significant spatial clustering of high-income households, and although most of that clustering takes place around the larger urban centres, there are substantial pockets of high-income households throughout the study area. Second, the maps show that the 100m bandwidth retains a large resolution even in the rural areas. Map 2.4 b shows the clustering of low income households, showing broadly an inverse pattern compared to map 2.4 a. For low income households we also observe clusters across the study area. Maps 2.4 c and 2.4 d show the percentages of households classified as respectively high and low outliers. As expected, the share of

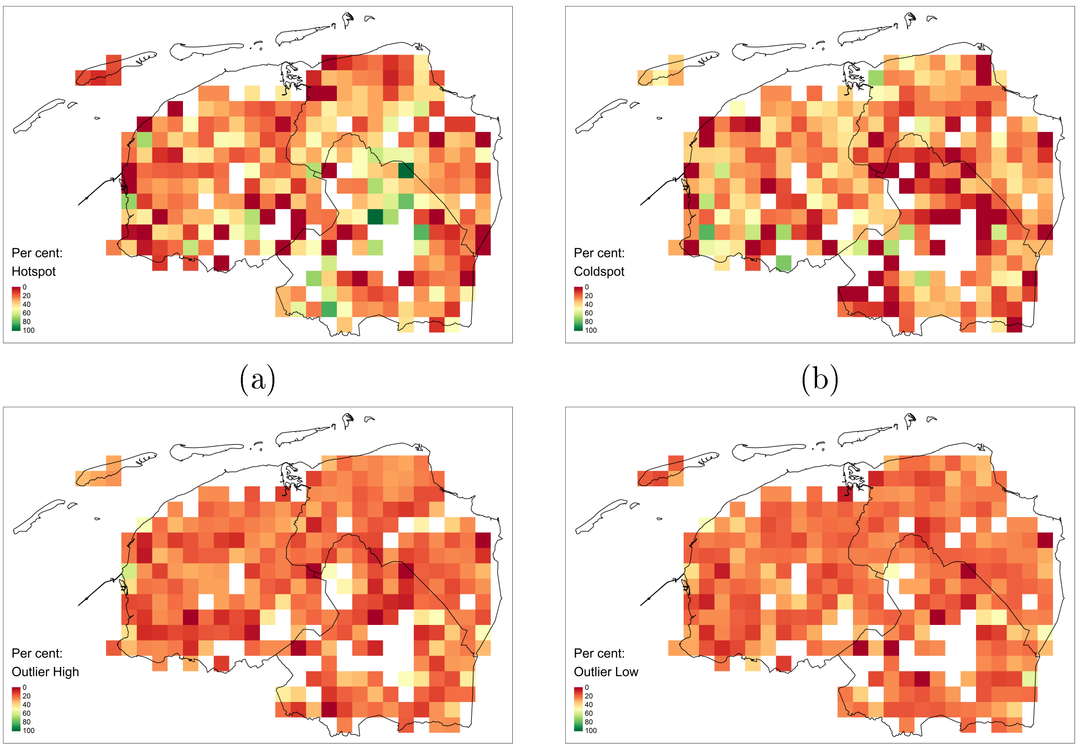
[3] The analyses were performed on individual cases. In order to protect the anonymity of the respondents, maps will only show rasterised outcomes on a 5 kilometre grid adapted to the research area. In addition, raster cells with fewer than ten respondents are left blank

Figure 2.3: Disposable household income distribution Lifelines



outliers is lower across the study area.

Figure 2.4: Distribution of disposable household income in clusters



(a) (b)

(c) (d)

2.5.3 Spatial regression results

When we add the relative income variable to the baseline model (table 2.4, showing concentric models) we find that relative income and SWB display a more complex and diverse interrelationship than a straightforward comparative utility model would predict. When living in a hotspot (that is, a cluster of high-income households), we find the effect on well-being to be negative. This is in line with the comparison theory hypothesis, where, controlling for household income, higher household income neighbours have a negative effect on individual well-being.

The coldspot, a cluster of low income households, shows a negative effect as well. This is contrary to the comparison effect. For a given household income, the peer-effect should be positive as the neighbourhood income is lower. Instead, we find that a less affluent neighbourhood has a negative externality on the well-being of the individual. For high-income oultiers, a lower household income for the neighbours corresponds to higher well-being for the individual. This is in line with the comparison effect of well-being again. For low-income outliers, we find no effect.

As we add progressively larger bandwidth models, we see that the relative positions in larger regions do not significantly affect SWB. The sign and significance of the coefficients for the smallest bandwidths remain the same (with the exception of high outliers), indicating that the peer-effect occurs on the smallest spatial scales.

Table 4: Spatial Regression Results Concentric Models

Using the concentric specification of the neighbourhood model and comparing the AICs we find the model probabilities in figure 2.5[4]. The first conclusion we draw from this is that the spatial model performs significantly better than the baseline model. Looking at tables 2.3 and 2.4 we see that the AIC drops from 312,579.4 in the baseline model, to 268,499.3 in the spatial model with the 100m distance threshold. This result shows that including the relative income to the neighbourhood improves the model significantly. We then look at which bandwidth specification provides the best fit. The model probabilities for the concentric specification show that the model with the smallest bandwidth is the most likely model. The model including both the 100-metre bandwidth and 250-metre bandwidth concentric rings has a likelihood ratio of 0.095, meaning this can't be rejected at the 0.05 level, although the AIC's suggest it is not an improvement. All subsequent models have model probabilities below 0.05.

Using the overlapping neighbourhoods, we arrive at the same conclusion, with in-

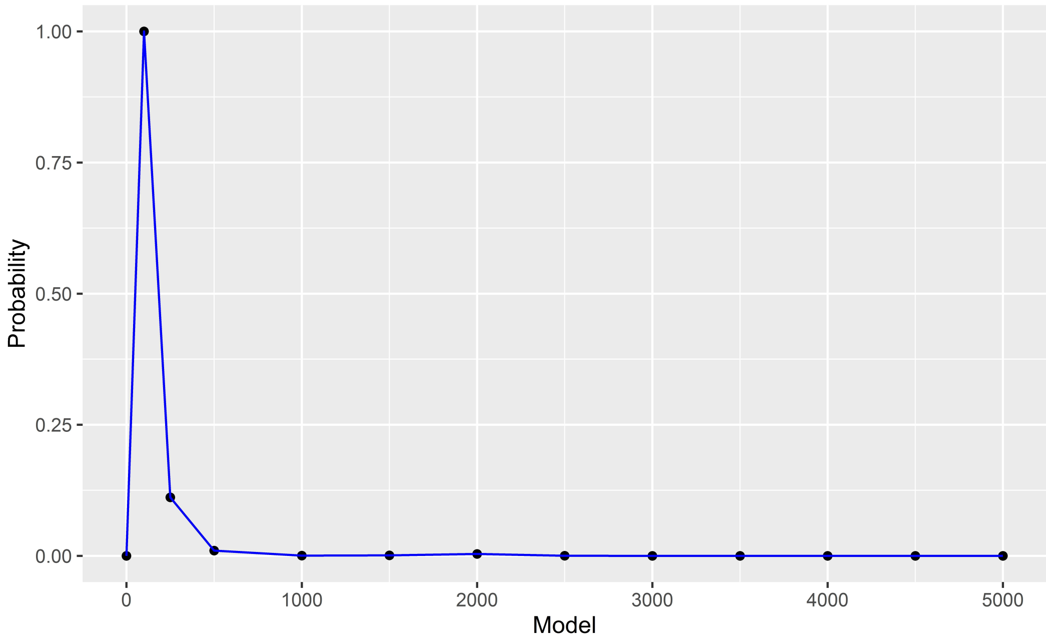
[4]The AICc is related to the number of cases in the model. For the concentric neighbour specification, more cases are excluded at the smaller nearest-neighbour bandwidths as they have empty neighbour sets. For the equivalent likelihood calculation a subset of the dataset was used excluding all incomplete cases

Table 2.4: Spatial Regression Results Concentric Models

Variable	BW 100	BW 250	BW 500	BW 1000
(Intercept)	48.439***	48.464***	48.425***	48.387***
σ	(0.631)	(0.645)	(0.65)	(0.653)
Baseline vars	Yes	Yes	Yes	Yes
Income	0.212***	0.231***	0.241***	0.248***
σ	(0.038)	(0.042)	(0.044)	(0.045)
Hotspot: 100	-0.548***	-0.445*	-0.438*	-0.435*
σ	(0.144)	(0.195)	(0.196)	(0.196)
Coldspot: 100	-0.613***	-0.561***	-0.557***	-0.559***
σ	(0.128)	(0.161)	(0.161)	(0.161)
High out: 100	0.501*	0.306	0.290	0.286
σ	(0.198)	(0.234)	(0.235)	(0.235)
Low out: 100	-0.022	0.038	0.028	0.027
σ	(0.202)	(0.245)	(0.245)	(0.245)
Hotspot: 250		-0.251	0.141	0.105
σ		(0.257)	(0.361)	(0.363)
Coldspot: 250		-0.070	0.003	0.018
σ		(0.244)	(0.341)	(0.342)
High out: 250		0.578	0.391	0.377
σ		(0.368)	(0.469)	(0.47)
Low out: 250		-0.199	-0.079	-0.086
σ		(0.369)	(0.512)	(0.513)
Hotspot: 500			-0.634	-0.313
σ			(0.394)	(0.506)
Coldspot: 500			-0.090	-0.275
σ			(0.385)	(0.536)
High out: 500			0.377	0.512
σ			(0.539)	(0.727)
Low out: 500			-0.202	-0.068
σ			(0.587)	(0.75)
Hotspot: 1000				-0.488
σ				(0.492)
Coldspot: 1000				0.278
σ				(0.52)
High out: 1000				-0.137
σ				(0.699)
Low out: 1000				-0.236
σ				(0.746)
R^2	0.670	0.670	0.670	0.670
AIC	268,499.3	268,504.0	268,509.0	268,515.6

*** - $p < 0.001$, ** - $p<0.01$, * - $p<0.05$, † - $p<0.10$

Figure 2.5: Model probabilities by neighbourhood bandwidth (concentric)



creasing bandwidth size reducing model probabilities. Finally, using the third type of model, the overlapping neighbourhood bandwidths with each distance bandwidth estimated separately, we find the same result, with the 100m distance threshold giving the optimum AIC.

2.6 Discussion and conclusions

The notion that the relative position of an individual regarding their surroundings forms an important part of well-being was first developed in order to address aspects of the Easterlin paradox (Easterlin, 1974) and this idea has since been used successfully to explain well-being in nations and regions (McBride, 2001; Luttmer, 2005). However, questions regarding the appropriate spatial scale of the reference group or the neighbourhood have so far not been addressed in the literature. Studies have typically opted for comparison groups based either on national or sub-national (but still large regional) specifications, or for specifications based on social characteristics such as education status, income, or employment. However, inter-personal comparisons are typically based on experience and this suggests that spatial proximity may have strong conditioning effects on the appropriate comparison groups, with geographically close neighbourhoods being especially important.

Our results suggest that individual well-being is indeed the result of comparisons to the neighbourhood, and the spatial extent of the comparisons is smaller than has been previously modelled. Our analysis demonstrates that the comparison effect is indeed significant at the 100m and, somewhat less, at the 250m distance threshold. Estimating the comparison effect on larger spatial scales still returns significantly better results than the simple non-comparative model, which is in line with previous empirical work, but these models perform significantly worse than the smallest neighbourhood specification. These results show that it is important to consider the spatial scale of the reference group when studying relative income. Moreover, these results indicate that operationalizing the reference group on a small spatial scale provides the best model fit. In addition, the comparison effect we find in this study is somewhat more complex than a straightforward comparative utility model would suggest. Our results suggest that people in households with higher than average (at the national level) incomes living in affluent areas are relatively less happy, which is in line with a comparative utility framework. However, we find no statistically significant negative effect for people living in affluent areas with below average household incomes. Meanwhile, in less affluent areas, people in households with higher incomes again report higher levels of well-being, as predicted by comparative utility. For lower income households in more affluent areas we find no significant effect. As such, the comparative utility arguments appear to hold for individuals with incomes above the national average, but not for those below the national average. It may be that the agreeable social or natural environments in affluent localities partially compensate for any adverse inter-personal comparison effects, while in poorer neighbourhoods the less agreeable environments tend to exacerbate any adverse inter-personal comparison effects. These observations suggest that some form of local externality effects may be operating, but exactly why this might be so, however, is for further research.

The results from our data show that the signs and significance of known confounders of SWB are plausible within the wider literature. There are some notable deviations, with age having a linear and negative association to SWB after controlling for the extensive set of personal confounders available in the Lifelines dataset. People experiencing more physical role limitations counterintuitively report higher SWB. Estimating a series of regressions with SWB on the left-hand side, and on the right-hand side physical role limitations and each of the other RAND constructs shows that the sign reversal for the coefficient of physical role limitations appears when combined with social functioning. A bivariate model of these two RAND constructs returns a coefficient of 0.85 (R^2 = 0.28), with both variables measured on a 0-100 scale. Although the VIFs are within the acceptable range for all models, a coefficient this close to 1 on the same scale means the negative coefficient of this variable should be treated with caution.

Our findings relating SWB with relative income are in line with Ma et al. (2018), who find a significant negative effect on life-satisfaction if respondents perceive themselves to have a lower income than peers in their neighbourhood. Interestingly, when this variable is included in their model the direct effect of income disappears entirely. In our model, the direct effect of income remains significant and positive. A possible explanation for this is that the survey used in Ma et al. (2018) specifies peers in the neighbourhood, thereby sub-setting the comparison to those deemed relevant by the respondent. In the present study, linking the individuals to peers through social networks or friend networks was not possible with the data. As a result, all individuals in the neighbourhood are included in the analysis. The differences in sign and coefficient are an interesting indication that there may be a negative SWB effect if individuals compare themselves to more aspirational reference groups.

Both the results in Ma et al. (2018) and in this study confirm the suspicions by Hicks and Hicks (2014) that observing positional goods, relative income, and conspicuous consumption are predominantly local phenomena. Our chapter is the first to expand on the negative externalities of relative deprivation (Luttmer, 2005) by adding a spatial dimension. The implications from this are that negative externalities of income inequality at small spatial scales generally remain unobserved. This outcome highlights the importance of analyzing SWB at highly disaggregated spatial scales. The asymmetrical relationship between relative income and specifically the lack of a peer-effect for individuals with lower household incomes are promising avenues for future research.